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1 %% Machine Learning
2 % Lab 7: Neural Network Training
3 % — Handwritten Digits —
4 %{
5 For this exercise, you will teach a neural network to
6 recognize handwritten digits (from 0 to 9). Automated handwritten digit
7 recognition is widely used today — from recognizing zip codes (postal codes)
8 on mail envelopes to recognizing amounts written on bank checks.
9 %}
10
11 %% Initialization
12 clear ; close all; clc
13
14 %% Setup the parameters you will use for this exercise
15 input_layer_size = 400; % 20x20 Input Images of Digits
16 hidden_layer_size = 25; % 25 hidden units
17 num_labels = 10; % 10 labels, from 1 to 10
18 % (note that we have mapped "0" to label 10)
19
20 %% ===== Part 1: Loading and Visualizing Data =====
21 % We start the exercise by first loading and visualizing the dataset.
22 % You will be working with a dataset that contains handwritten digits.
23 %
24
25 % Load Training Data
26 fprintf('Loading and Visualizing Data ...\n')
27
28 load('ex4data1.mat');
29 m = size(X, 1);
30
31 % Randomly select 100 data points to display
32 sel = randperm(size(X, 1));
33 sel = sel(1:100);
34
35 displayData(X(sel, :));
36
37 fprintf('Program paused. Press enter to continue.\n');
38 pause;
39
40
41
42 %% ===== Part 2: Loading Parameters =====
43 % In this part of the exercise, we load some pre-initialized
44 % neural network parameters.
45
46 fprintf('\nLoading Saved Neural Network Parameters ...\n')
47
48 % Load the weights into variables Theta1 and Theta2
49 load('ex4weights.mat');
50 w1 = Theta1;
51 w2 = Theta2;
52
53 % Unroll parameters
54 nn_params = [w1(:) ; w2(:)];
55
56 %% ===== Part 3: Compute Cost (Feedforward) =====

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57 % To the neural network, you should first start by implementing the
58 % feedforward part of the neural network that returns the cost only. You
59 % should complete the code in nnCostFunction.m to return cost. After
60 % implementing the feedforward to compute the cost, you can verify that
61 % your implementation is correct by verifying that you get the same cost
62 % as us for the fixed debugging parameters.
63 %
64 % We suggest implementing the feedforward cost *without* regularization
65 % first so that it will be easier for you to debug. Later, in part 4, you
66 % will get to implement the regularized cost.
67 %
68 fprintf('\nFeedforward Using Neural Network ...\n')
69
70 % Weight regularization parameter (we set this to 0 here).
71 lambda = 0;
72
73 C = nnCostFunction(nn_params, input_layer_size, hidden_layer_size, ...
74                   num_labels, X, y, lambda);
75
76 fprintf(['Cost at parameters (loaded from ex4weights): %f '...
77         '\n(this value should be about 0.287629)\n'], C);
78
79 fprintf('\nProgram paused. Press enter to continue.\n');
80 pause;
81
82 %% ===== Part 4: Implement Regularization =====
83 % Once your cost function implementation is correct, you should now
84 % continue to implement the regularization with the cost.
85 %
86
87 fprintf('\nChecking Cost Function (w/ Regularization) ... \n')
88
89 % Weight regularization parameter (we set this to 1 here).
90 lambda = 1;
91
92 C = nnCostFunction(nn_params, input_layer_size, hidden_layer_size, ...
93                   num_labels, X, y, lambda);
94
95 fprintf(['Cost at parameters (loaded from ex4weights): %f '...
96         '\n(this value should be about 0.383770)\n'], C);
97
98 fprintf('Program paused. Press enter to continue.\n');
99 pause;
100
101
102 %% ===== Part 5: Sigmoid Gradient =====
103 % Before you start implementing the neural network, you will first
104 % implement the gradient for the sigmoid function. You should complete the
105 % code in the sigmoidGradient.m file.
106 %
107
108 fprintf('\nEvaluating sigmoid gradient...\n')
109
110 g = sigmoidGradient([-1 -0.5 0 0.5 1]);
111 fprintf('Sigmoid gradient evaluated at [-1 -0.5 0 0.5 1]:\n ');
112 fprintf('%f ', g);
113 fprintf('\n\n');

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114
115 fprintf('Program paused. Press enter to continue.\n');
116 pause;
117
118
119 %% ===== Part 6: Initializing Pameters =====
120 % In this part of the exercise, you will be starting to implment a two
121 % layer neural network that classifies digits. You will start by
122 % implementing a function to initialize the weights of the neural network
123 % (randInitializeWeights.m)
124
125 fprintf('\nInitializing Neural Network Parameters ...\n')
126
127 init_w1 = randInitializeWeights(input_layer_size, hidden_layer_size);
128 init_w2 = randInitializeWeights(hidden_layer_size, num_labels);
129
130 % Unroll parameters
131 initial_nn_params = [init_w1(:) ; init_w2(:)];
132
133 %% ===== Part 7: Implement Regularization =====
134 % Once your backpropagation implementation is correct, you should now
135 % continue to implement the regularization with the cost and gradient.
136 %
137
138 fprintf('\nChecking Backpropagation (w/ Regularization) ... \n')
139
140 lambda = 3;
141
142 % Also output the costFunction debugging values
143 debug_C = nnCostFunction(nn_params, input_layer_size, ...
144                         hidden_layer_size, num_labels, X, y, lambda);
145
146 fprintf(['\n\nCost at (fixed) debugging parameters (w/ lambda = %f): %f ' ...
147         '\n(for lambda = 3, this value should be about 0.576051)\n\n'], lambda,
148         debug_C);
149
150 fprintf('Program paused. Press enter to continue.\n');
151 pause;
152
153 %% ===== Part 9: Training NN =====
154 % You have now implemented all the code necessary to train a neural
155 % network. To train your neural network, we will now use "fmincg", which
156 % is a function which works similarly to "fminunc". Recall that these
157 % advanced optimizers are able to train our cost functions efficiently as
158 % long as we provide them with the gradient computations.
159 %
160 fprintf('\nTraining Neural Network... \n')
161
162 % After you have completed the assignment, change the MaxIter to a larger
163 % value to see how more training helps.
164 options = optimset('MaxIter', 50);
165
166 % You should also try different values of lambda
167 lambda = 1;
168
169 % Create "short hand" for the cost function to be minimized

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170 costFunction = @(p) nnCostFunction(p, ...
171                                     input_layer_size, ...
172                                     hidden_layer_size, ...
173                                     num_labels, X, y, lambda);
174
175 % Now, costFunction is a function that takes in only one argument (the
176 % neural network parameters)
177 [nn_params, cost] = fmincg(costFunction, initial_nn_params, options);
178
179 % Obtain w1 and w2 back from nn_params
180 w1 = reshape(nn_params(1:hidden_layer_size * (input_layer_size + 1)), ...
181              hidden_layer_size, (input_layer_size + 1));
182
183 w2 = reshape(nn_params((1 + (hidden_layer_size * (input_layer_size + 1))):end), ...
184              num_labels, (hidden_layer_size + 1));
185
186 fprintf('Program paused. Press enter to continue.\n');
187 pause;
188
189
190 %% ===== Part 9: Visualize Weights =====
191 % You can now "visualize" what the neural network is learning by
192 % displaying the hidden units to see what features they are capturing in
193 % the data.
194
195 fprintf('\nVisualizing Neural Network... \n')
196
197 displayData(w1(:, 2:end));
198
199 fprintf('\nProgram paused. Press enter to continue.\n');
200 pause;
201
202 %% ===== Part 10: Implement Predict =====
203 % After training the neural network, we would like to use it to predict
204 % the labels. You will now implement the "predict" function to use the
205 % neural network to predict the labels of the training set. This lets
206 % you compute the training set accuracy.
207
208 pred = predict(w1, w2, X);
209
210 fprintf('\nTraining Set Accuracy: %f\n', mean(double(pred == y)) * 100);

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1 function [C grad] = nnCostFunction(nn_params, ...
2                                     input_layer_size, ...
3                                     hidden_layer_size, ...
4                                     num_labels, ...
5                                     X, y, lambda)
6 %NNCOSTFUNCTION Implements the neural network cost function for a two layer
7 %neural network which performs classification
8
9 % Reshape nn_params back into the parameters weight1 and weight2, the weight
   matrices
10 % for our 2 layer neural network
11 w1 = reshape(nn_params(1:hidden_layer_size * (input_layer_size + 1)), ...
12              hidden_layer_size, (input_layer_size + 1));
13
14 w2 = reshape(nn_params((1 + (hidden_layer_size * (input_layer_size + 1))):end), ...
15              num_labels, (hidden_layer_size + 1));
16
17 % Setup some useful variables
18 m = size(X, 1);
19
20 % You need to return the following variables correctly
21 C = 0;
22 w1_grad = zeros(size(w1));
23 w2_grad = zeros(size(w2));
24
25 A1 = [ones(size(X,1),1) X];
26 S2 = A1*w1';
27 A2 = sigmoid(S2);
28 A2_0 = [ones(size(A2,1),1) A2];
29 S3 = A2_0*w2';
30 A3 = sigmoid(S3);
31
32 HX = A3;
33
34 % recode y to Y // TRICKY => ONE HOT ENCODING
35 I = eye(num_labels);
36 Y = zeros(m, num_labels);
37
38 for i=1:m
39     Y(i, :) = I(y(i), :);
40 end
41
42 penalty = (lambda / (2*m)) * (sum(sum(w1(:, 2:end).^2, 2)) + sum(sum(w2(:, 2:end).^2, 2)
   ));
43
44 C = (1/m) * sum(sum((-Y).*log(HX) - ((1-Y).*log(1-HX)))) + penalty;
45
46 % calculate sigmas //DELTAS
47 sigma3 = (A3-Y);
48 sigma2 = (sigma3*w2).*sigmoidGradient([ones(size(S2, 1), 1) S2]);
49 sigma2 = sigma2(:, 2:end);
50
51 % accumulate gradients
52 delta_1 = (sigma2'*A1);
53 delta_2 = (sigma3'*A2_0);
54

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55 % calculate regularized gradient
56 p1 = (lambda/m)*[zeros(size(w1, 1), 1) w1(:, 2:end)];
57 p2 = (lambda/m)*[zeros(size(w2, 1), 1) w2(:, 2:end)];
58 w1_grad = delta_1./m + p1;
59 w2_grad = delta_2./m + p2;
60
61 % Unroll gradients
62 grad = [w1_grad(:) ; w2_grad(:)];
63
64 end

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sigmoidGradient.m

```

1 function g = sigmoidGradient(z)
2 %SIGMOIDGRADIENT returns the gradient of the sigmoid function
3 %evaluated at z
4
5 g = zeros(size(z));
6 g = sigmoid(z).*(1-sigmoid(z));
7
8 end

```

randInitializeWeights.m

```

1 function W = randInitializeWeights(L_in, L_out)
2 %RANDINITIALIZEWEIGHTS Randomly initialize the weights of a layer with L_in
3 %incoming connections and L_out outgoing connections
4 % Note that W should be set to a matrix of size(L_out, 1 + L_in) as
5 % the first column of W handles the "bias" terms
6
7 W = zeros(L_out, 1 + L_in);
8 % Initialize W randomly so that we break the symmetry while
9 % training the neural network.
10
11 epsilon_init = 0.12;
12 W = rand(L_out, 1 + L_in) * 2 * epsilon_init - epsilon_init;
13
14 end

```

predict.m

```

1 function p = predict(w1, w2, X)
2 %PREDICT Predict the label of an input given a trained neural network
3 % p = PREDICT(w1, w2, X) outputs the predicted label of X given the
4 % trained weights of a neural network (w1, w2)
5
6 % Useful values
7 m = size(X, 1);
8 num_labels = size(w2, 1);
9
10 % You need to return the following variables correctly
11 p = zeros(size(X, 1), 1);
12
13 h1 = sigmoid([ones(m, 1) X] * w1');
14 h2 = sigmoid([ones(m, 1) h1] * w2');
15 [dummy, p] = max(h2, [], 2);
16
17 end

```